

12-2006

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Original investigation correlated joint fluctuations can influence the selection of steady state gait patterns in the elderly

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Abstract

This investigation utilized a Markov model to investigate the relationship of correlated lower extremity joint fluctuations and the selection of a steady state gait pattern in the young and elderly. Our model simulated the neuromuscular system by predicting the behavior of the joints for the next gait cycle based on the behavior exhibited in the preceding gait cycles. Such dependencies in the joint fluctuations have been noted previously in the literature. We speculated that compared to the young model, the characteristics of the correlated fluctuations in the elderly model would result in the selection of a different steady state gait pattern. The results of our simulation support the notion that correlated fluctuations in the joint kinematics influence the selection of a steady state gait pattern. The steady state gait pattern for the elderly model was dependent the ankle and hip. Conversely, the steady state gait pattern for the young control model was dependent on the behavior of the knee and hip. Based on our model, we suggested that the altered steady state gait patterns observed in the elderly may be due to an altered neuromuscular memory of prior joint behaviors.

Keywords: Variability; Aging; Gait; Markov modeling; Nonlinear dynamics

1. Introduction

The neuromuscular system's ability to control movement patterns declines as an individual age. A decline in neuromuscular function has been suggested to be an important indicator of falls in the aging population [1]. It has been well documented that the diminished capacity of the elderly neuromuscular system results in a gait pattern that has a shorter gait cycle time interval, a decreased step length and differences in joint kinematics [1–10]. However, beyond this descriptive information, little is known regarding changes in the control mechanisms of the neuromuscular system that are responsible for the characteristics of elderly gait patterns.

Several investigations have suggested that variations in the gait kinematics may offer insights on the control mechanisms of the elderly gait [4, 8, 9]. In particular, it has been shown that the elderly gait patterns exhibit increased kinematic variability [4, 8, 9, 11]. It has been suggested that this increased variability is due to the diminished capacity of the elderly neuromuscular system to produce a functional gait pattern and it has been perceived as "error" in the neuromuscular system [9]. Based on this notion, an increased amount of error (or variability) in the gait pattern results in a less stable movement pattern that is more susceptible to falls [4, 8, 9]. However, the degree of error that is acceptable for a stable gait pattern remains unknown.

Recent investigations have indicated that cycle-to-cycle variations in the lower extremity gait kinematics may not be error in the neuromuscular system. This notion is based on scientific evidence that these variations in the gait pattern have a fractal structure [12–17]. A fractal structure indicates that

subtle cycle-to-cycle fluctuations are not random error in the system. Rather these fluctuations are correlated with previous kinematic behaviors that have occurred during the gait pattern. The presence of correlated fluctuations have been noted in the literature for the stride interval [12–15] and knee joint kinematics [11, 16, 17] during gait. Additionally, recent investigations have indicated stride-to-stride correlated fluctuations are altered in the elderly [11, 14]. The nature of these correlated fluctuations during gait appears to be dependent on the health of the neuromuscular system [11, 14]. It is possible that the selection of a steady state gait in the elderly is affected by alterations in the cycle-to-cycle correlated fluctuations. With interest in determining the neuromuscular control mechanisms of elderly gait, further research is necessary to elucidate the relationship between correlated gait fluctuations and steady state gait patterns.

Markov models have been used in a wide variety of experimental situations to describe the long-term behavior of a system that performs a task many times in a similar way [18, 19]. Change in the behavior of the model from one state to the next is dependent on the preceding states. Hence, the behavior of the system in the next state is correlated with the behavior of the system in the preceding state. The controlling factor for changes in the behavior of the model is the transition probability matrix. The transition probability matrix contains the conditional probabilities for each component of the system to move to a new state on the next iteration [18, 19]. As time progresses, fluctuations in the behavior of the system from one state to the next exponentially decay to a steady state that describes the long-term behavior of the system [18, 19]. Since a Markov model can simulate the influence of previous states on future states and the selection of a steady state behavior, this model may offer further insights on the relationship between the correlated fluctuations observed in human gait and the selection of a steady state gait pattern.

As a step toward understanding the neuromuscular control mechanisms associated with the elderly gait, we utilized a Markov model to investigate the relationship of the correlated joint fluctuations and the selection of a steady state gait pattern. We speculated that the characteristics of the correlated joint fluctuations from one state to the next in the elderly Markov model would result in a steady state gait pattern that was different from the young controls.

2. Materials and Methods

Participants of this investigation included young control ($N = 10$; age = 25.1 ± 5.3 years, range = 20–37 years) and elderly ($N = 10$; age = 74.6 ± 2.5 years, range = 71–79 years) subjects who had prior treadmill walking experience. The elderly subjects included in this investigation met the following criteria: independent ambulation (i.e. no assistive devices), independent living in the community, no neurological pathology, no acute illness, no use of medications that will affect gait performance and no restrictions in activities of daily living. Screening of the elderly subjects for neuromuscular deficiencies was performed by a licensed physical therapist. All of our subjects met the above criteria and none were excluded from this investigation. Prior to testing, each subject read and signed an informed consent that was approved by the University Institutional Review Board.

The subjects walked on a treadmill wearing their own comfortable footwear, while sagittal kinematic data of the right lower extremity were collected using a 60 Hz high-speed video camera. A single camera was used in this investigation because sagittal plane measures correspond well in two and three dimensions [20, 21]. Prior to videotaping, reflective markers were positioned on the subject's right lower extremity. All positional markers were placed on the subjects by the same examiner. Sagittal plane markers placement were as follows: (a) greater trochanter, (b) axis of the knee joint as defined by the alignment of the lateral condyles of the femur, (c) lateral malleolus, (d) outsole of the shoe approximately at the bottom of the calcaneus and (e) outsole of the shoe approximately at the fifth metatarsal head.

The subjects were allowed to warm-up for a minimum of 8 min. This duration of warm-up has been considered sufficient for individuals to achieve a proficient treadmill movement pattern [22]. During the warm-up session, each subject established a self-selected comfortable walking pace (see Table 1 for subjects' walking speeds). Subjects were instructed to select a pace that would be similar to a pace that they would use when performing continuous aerobic walking. Collection of data did not occur until the subject stated that they felt comfortable and could maintain the self-selected pace for a long duration. Once the subject felt comfortable walking on the treadmill, 15 consecutive gait cycles (trials) were collected per subject.

The obtained kinematic positional coordinates from the sagittal markers were smoothed using a Butterworth low-pass filter with a selective cut-off based on the Jackson algorithm [23]. Using this algorithm, the residual difference between raw data and the data filtered with various cut-off frequencies was initially determined. This was followed by the construction of a polynomial where the various cut-off frequencies were on the abscissa and the associated percent average residuals were on the ordinate. The second derivative of this polynomial was found at each cut-off frequency. The cut-off frequency was then considered optimal if its second derivative fell beneath the prescribed limit of 0.0001. Using this algorithm, the cut-off frequency values for the respective raw position data ranged from 6 to 10 Hz. From the filtered coordinates, the sagittal foot, shank and thigh angular displacements were calculated relative to the right horizontal axis. Calculation of the ankle, knee and hip joint angles for each gait cycle was based on an absolute approach: $\Phi_{\text{ankle}} = \Phi_{\text{foot}} - \Phi_{\text{leg}} - 90$; $\Phi_{\text{knee}} = \Phi_{\text{thigh}} - \Phi_{\text{leg}}$; $\Phi_{\text{hip}} = \Phi_{\text{thigh}} - 90$.

Table 1
Means and standard deviations for the elderly and young groups used to construct the two Markov models

| Group | Range of motion (°) | | | Walking speed (m s^{-1}) |
|---------|---------------------|------------|-------------|-------------------------------------|
| | Ankle | Knee | Hip | |
| Young | 32.8 (6.7) | 73.9 (8.6) | 38.3 (3.1) | 1.1 (0.2) |
| Elderly | 23.0 (6.3) | 72.5 (8.6) | 34.9 (10.9) | 0.8 (0.2) |

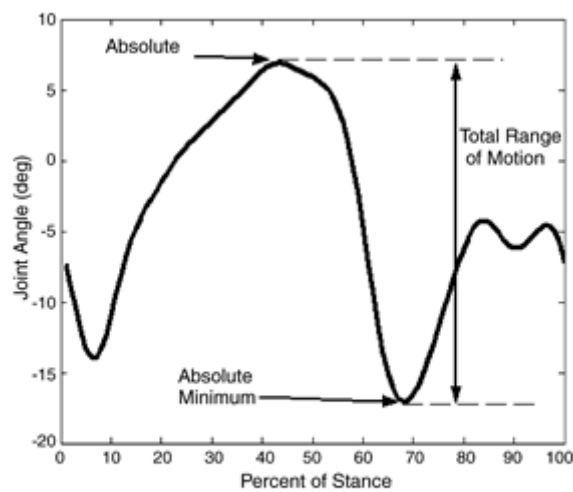


Fig. 1. The definition used for the calculation of the joint range of motion based on the absolute minimum and maximum. The kinematic chart represented here is an example of the ankle's range of motion.

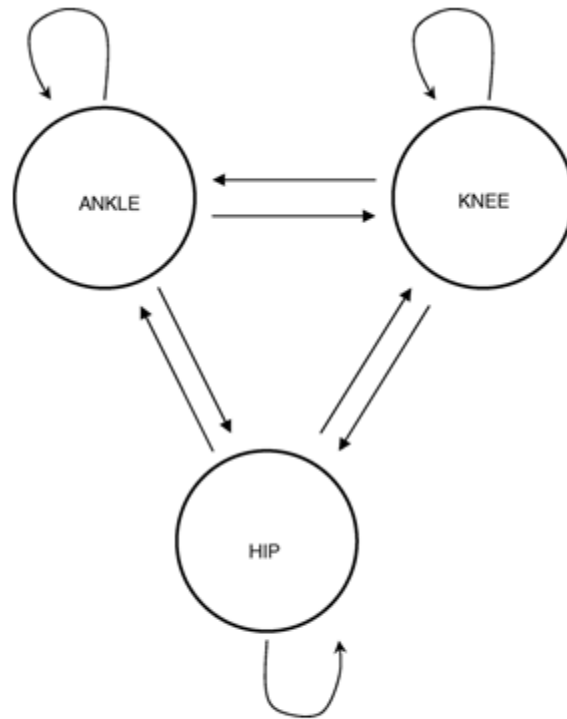


Fig. 2. Directed graph that represents the Markov model. The vertices (circles) represent the current state of the joint for the i th gait cycle, and the edges (arrows) represent the probability of the joint to change its behavior for the next gait cycle.

The gait cycles were separated for analysis via custom laboratory software. With this software, the derivatives of the heel marker displacement, along with visual inspection of the stick figure were utilized to determine the respective heel contacts of the gait cycle. Similar algorithms have proven to be robust in determining heel and toe-off timings [24].

The respective joint angular displacements were normalized to 100 points per gait cycle using a cubic spline routine. The total range of motion (ROM) was determined from the absolute difference of the absolute maximum and absolute minimum of the respective joint angle curves (Fig. 1).

The joint ROMs from all subjects in the respective groups were used to develop two Markov models that simulated the behavior of the young and elderly lower extremity during gait. The Markov model used in this investigation is detailed by the directed graph presented in Fig. 2. The vertices of the directed graph contain the current state of the joint for the i th gait cycle, and the edges of the directed graph represent the probability of the joint to change its behavior for the next gait cycle. The edges of the model were bi-directional. This indicates that the transient behavior of our model was based on joint interactions. Additionally, edges in the model return to the original vertex. Therefore, transient behavior was also dependent on the behavior of the joint itself. Based on the outlay of our model, variations in the behavior of the system from one gait cycle to the next were based on probability relationships.

The probabilities associated with each of the edges of the directed graph were determined from forward selection regression equations created for each group. The ankle joint ROM was regressed on the knee ROM and hip ROM, the knee joint ROM was regressed on the ankle ROM and hip ROM, and the hip joint ROM was regressed on the knee ROM and ankle ROM. The ROMs from all gait cycles from the respective groups were utilized to create the respective regression equations. Hence, each regression equation was based on 150 gait cycles for each group. As predictors were added to the regression

equation, the change in the coefficient of determination (e.g. ΔR^2) was used to develop the probability vectors. Additionally, the remaining unexplained variance ($1 - R^2$) of the regression equation was attributed to the behavior of the regressed joint independent of the behavior of the other lower extremity joints. Exemplar R^2 values for the ankle were as follows:

$$\begin{aligned} \text{AnkleROM} &= \alpha + \beta_1 \text{KneeROM}, \quad R^2_{AK} \\ \text{AnkleROM} &= \alpha + \beta_1 \text{KneeROM} + \beta_2 \text{HipROM}, \quad \Delta R^2_{AH} \\ & \quad (1 - R^2)_{AA} \end{aligned}$$

where R^2_{AK} represents the variance accounted for by the knee joint ROM, ΔR^2_{AH} represents the additional variance accounted for by the hip joint ROM and $(1 - R^2)_{AA}$ represents the remaining unexplained variance accounted for by the ankle. These probabilities represented the edges of the graph (Fig. 2) and were contained in the transition probability matrix (M) (Eq. (1)) where subscript A represents the ankle, subscript K represents the knee and subscript H represents the hip. Column one of the respective transition probability matrix represented the behavior of the ankle, column two represented the behavior of the knee and column three represented the behavior of the hip. The diagonal of the transition probability matrix represented the contribution of the joint in selecting its behavior in future states independent of the other joints (i.e. an edge that returns to its vertex in Fig. 2). All other cells of the matrix represented the contribution of the other joints in determining the behavior of the joint in future states (i.e. bi-directional edges in Fig. 2).

$$M = \begin{bmatrix} (1 - R^2)_{AA} & \Delta R^2_{KA} & \Delta R^2_{HA} \\ \Delta R^2_{AK} & (1 - R^2)_{KK} & \Delta R^2_{HK} \\ \Delta R^2_{AH} & \Delta R^2_{KH} & (1 - R^2)_{HH} \end{bmatrix}$$

The Markov models for the young controls and elderly were simulated for a sequence of gait cycles until a steady state gait pattern was achieved (Eq. (2)).

$$\mathbf{X}_{k+1} = M\mathbf{X}_k \quad \text{for } k = 0, 1, 2, \dots \quad (2)$$

\mathbf{X}_k in the model was the steady state vector of the system for the k th gait cycle (i.e. $\mathbf{X}^T = [\text{ankle joint ROM, knee joint ROM, hip joint ROM}]$) and M was the transition probability matrix as describe above. M remained fixed throughout the simulation. The components of \mathbf{X}_k represented the vertices of the directed graph (Fig. 2) and contained the percent contribution of each of the joints for the respective gait cycle. \mathbf{X}_0 was set to unity (e.g. $[1, 0, 0]^T$) at the start of the simulation [18,19]. Differences between the two models were evident by inspecting the \mathbf{X}_k after the respective system converged to a steady state. A steady state was evident when the values of \mathbf{X}_k were not changing from one k to the next for four decimal places. The components of the respective \mathbf{X}_k were then expressed as percentages. Different percentages between the two models suggested different steady state gait strategies. A larger percentage in one of the components of \mathbf{X}_k indicates that the steady state gait pattern was more dependent on the performance of the respective joint.

3. Results

Representative data from the two groups that was used to construct the Markov models are presented in Table 1. The transition probability matrices developed from the elderly and young data were as follows:

$$M_{\text{Elderly}} = \begin{bmatrix} 0.56 & 0.82 & 0.41 \\ 0.03 & 0.04 & 0.10 \\ 0.41 & 0.14 & 0.49 \end{bmatrix}$$

$$M_{\text{Young}} = \begin{bmatrix} 0.80 & 0.05 & 0.04 \\ 0.02 & 0.19 & 0.76 \\ 0.18 & 0.76 & 0.20 \end{bmatrix}$$

where M_{Elderly} is the transition probability matrix for the elderly group, M_{Young} the transition probability matrix for the young control group. A numerical simulation for the young Markov model was as follows:

$$\mathbf{X}_1 = M\mathbf{X}_0 = \begin{bmatrix} 0.80 & 0.05 & 0.04 \\ 0.02 & 0.19 & 0.76 \\ 0.18 & 0.76 & 0.20 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.8000 \\ 0.0200 \\ 0.1800 \end{bmatrix}$$

$$\mathbf{X}_2 = M\mathbf{X}_1 = \begin{bmatrix} 0.80 & 0.05 & 0.04 \\ 0.02 & 0.19 & 0.76 \\ 0.18 & 0.76 & 0.20 \end{bmatrix} \begin{bmatrix} 0.8000 \\ 0.0200 \\ 0.1800 \end{bmatrix} = \begin{bmatrix} 0.6482 \\ 0.1566 \\ 0.1952 \end{bmatrix}$$

$$\mathbf{X}_3 = M\mathbf{X}_1 = \begin{bmatrix} 0.80 & 0.05 & 0.04 \\ 0.02 & 0.19 & 0.76 \\ 0.18 & 0.76 & 0.20 \end{bmatrix} \begin{bmatrix} 0.6482 \\ 0.1566 \\ 0.1952 \end{bmatrix} = \begin{bmatrix} 0.5342 \\ 0.1911 \\ 0.2747 \end{bmatrix}$$

⋮

⋮

⋮

$$\mathbf{X}_k = M\mathbf{X}_{k-1} = \begin{bmatrix} 0.80 & 0.05 & 0.04 \\ 0.02 & 0.19 & 0.76 \\ 0.18 & 0.76 & 0.20 \end{bmatrix} \begin{bmatrix} 0.1832 \\ 0.3977 \\ 0.4191 \end{bmatrix} = \begin{bmatrix} 0.1832 \\ 0.3977 \\ 0.4191 \end{bmatrix}$$

where the final X_k was the steady state for the young group. A similar method was used to simulate the elderly Markov model. The differences in the steady state gait patterns for the two group models indicated that the dependencies of the joint kinematics from one gait cycle to the next were affected by age (Table 2). The steady state gait pattern for the elderly model indicated that the correlated fluctuations in the gait cycle resulted in a gait pattern that was dependent primarily

Table 2
Steady state gait patterns for the elderly and young control Markov models

| | Ankle (%) | Knee (%) | Hip (%) |
|---------|-----------|----------|---------|
| Elderly | 52 | 6 | 42 |
| Young | 18 | 40 | 42 |

The percentages represent the contribution of each joint in the selected gait patterns. Differences in the percentages indicate different strategies for the steady state gait pattern.

on the behavior of the ankle (52%), and secondarily on the behavior of the hip (42%). Conversely, the steady state gait pattern for the young controls suggested that correlated fluctuations in the gait cycle resulted in a gait pattern that was more equally dependent on the behavior of the knee (40%) and hip (42%).

Discussion

The results of our Markov model suggested that the characteristics of the joint fluctuations can influence the selection of a steady state gait pattern. This notion was supported by the results of our models where the young control and elderly models had different steady state gait patterns (see Table 2). Prior investigations have described the gait patterns of the elderly as having altered ankle and hip joint movement patterns [1, 6, 7, 10]. Additionally, Kerrigan et al. [10] have noted that an altered ankle and hip joint movement patterns persist in the elderly regardless of walking speed. Our elderly model confirms these observations where the steady state gait pattern was dependent on the behavior of the ankle and hip (see Table 2). However, based on the results of our model, we suggest that correlated joint fluctuations may be an important control mechanism that is involved in the selection of such steady state gait patterns. This notion is based on the fact that fluctuations in the model from one state to the next lead to a gait pattern that was dependent on the ankle and hip.

Potentially the correlation between joint behaviors from one gait cycle to the next may be related to some sort of neuromuscular memory of prior lower extremity joint behaviors. Such memories may be an important control mechanism for selection of a steady state gait pattern. This is based on the fact that the steady state matrix (X_k) of the Markov model from one gait cycle to the next was dependent on the organization of the neuromuscular system in the previous gait cycle (X_{k-1}). Therefore, the behavior of the joints in the previous gait cycle may influence the behavior of the joints in the next state. There is considerable scientific evidence that neuromuscular memory of motor tasks have a neural representation in the prefrontal cortex and cerebellum [25, 26]. Additionally, it is apparent that these neural representations are dynamically created and adjusted to accommodate the ever changing environmental stimulus [27]. Such neural connectivity may serve as the biological constructs responsible for the correlated joint fluctuations noted in previous investigations [11–17]. Based on the results of our model, an altered neuromuscular memory of past joint behaviors during gait may be responsible for the selection of a different steady state gait patterns in the elderly. It is possible that neuro-physiological changes associated with aging [28–32] may cause a breakdown in the selection of neural pathways responsible for neuromuscular memory [11]. Additionally, it can be suggested that these neurophysiological changes may hinder the ability of the elderly to use sensory cues to recall neuromuscular memories of prior joint behaviors during gait. Further investigations are necessary to determine the relationship of neuromuscular memory and the observed correlated joint fluctuations during gait.

Several investigations have suggested that control of locomotor patterns are governed in part by passive dynamic biomechanical factors found in the muscles, connective tissues and ligaments [33–36]. Based on this notion, it is possible that correlated fluctuations may also be related to passive dynamic factors from the previous gait cycle. Investigations of animal locomotion have indicated that slow moving gait patterns are more dependent on neural control while faster gait patterns have a greater dependency on passive dynamic factors for control [33–36]. Potentially, the loss of viscoelastic properties in the musculoskeletal system of the aging may be related a greater reliance on the neural control mechanism. As such, this may be the reason we have noted altered correlated fluctuations at a slower gait pattern in the elderly. However, the extent that passive dynamic factors play a role in correlated fluctuations in gait and the greater reliance on neural control mechanisms in the elderly is currently unknown.

Markov modeling techniques are based on probability relationships that are assumed to represent real life behaviors. In this investigation, we assumed that the respective transition probability matrix (M) created from forward selection regression techniques accurately represented our subjects and were able to capture the relationship of one gait cycle to the next. We also assumed that the behavior of the lower extremity can be described by the directed graph in Fig. 2. In our model, the

outcome of the system was only dependent on the interaction and independent behaviors of the lower extremity joints. It is possible that other hidden variables (e.g. torso and upper extremity) that are not taken into account in our model may influence the outcome of the system. Additionally, we cannot currently state that the results of our model are independent of the walking speed selected by the respective groups. Furthermore, since a single model was used to explore each age group, we assumed that all subjects within each age group exhibited similar motor behavior. Although these limitations exist in the model, this investigation is an initial step toward understanding the influence of correlated joint fluctuations on the selection of steady state gait patterns.

In conclusion, this modeling approach tended to support the notion that further investigations of correlated fluctuations may offer promising insights about the control mechanisms of the neuromuscular system during gait. Our model indicated that correlated fluctuations in the joint kinematics from one gait cycle to the next may influence the selection of a steady state gait pattern. We suggest that the different steady state gait patterns observed in the elderly may be due to an altered neuromuscular memory of prior joint behaviors. The results of our Markov model should motivate further interest in exploring the relationship of kinematic variations and the selection of a steady state gait pattern. Further investigations are necessary to determine if the differences seen in our model are related to the deterioration of neuromuscular memory in the elderly or the loss of sensory cues to recall neuromuscular memories of prior joint behaviors during gait. Additionally, scientific questions should address if correlated joint fluctuations in the aging can be altered by a change in passive dynamic biomechanical factors found in the viscoelastic properties of the musculoskeletal system.

Acknowledgements

This research was funded in part by the Rhoden Biological Fellowship and NASA Statewide fellowship granted to M.J.K. and the Nebraska Research Initiative Grant awarded to N.S.

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